Algorithm for Identifying Writing Stroke and Direction

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Abstract—**Handwriting difficulty is a type of learning disability that may not be detected easily and its diagnosis requires special qualification and experience. Therefore, a new evaluation method is proposed to assist in detecting handwriting problems. This method uses computerized handwriting assessment based on the identification of errors in stroke type, sequences, and direction when forming Latin alphabets. This paper discusses an algorithm to identify type and direction of stroke based on xy-coordinate inputs. The algorithm starts with classification of input into three categories of stroke patterns, which are simple straight line, complex straight line, and curve line. The type and direction of stroke will then be determined by analysis of relationship between consecutive point and also angle difference between points. The algorithm works well in classification and identification involving straight line inputs, while improvements are needed in analyzing curve lines and complex lines involving smooth corner.**

Keywords-handwriting assessment; stroke recognition; handwriting difficulty

I. INTRODUCTION

Handwriting difficulty (HWD), also known as dysgraphia, is a type of learning disability that affects children's ability to express themselves through proper written language [1]. It is referred to as "a severe difficulty in producing handwriting that is legible and written at an age-appropriate speed" by Council of Exceptional Children, CEC of United States [2]. Children who suffer from HWD most commonly possess signs such as requiring longer duration than peers to complete written task given, unorganized and messy works, or relatively higher rate of spelling errors [3]. In addition, low legibility of written words, or even the feeling of frustration, lack of motivation and reluctance towards handwriting task, and inability to concentrate are other symptoms that point towards HWD [3], [4]. Unfortunately, identification of student with HWD is a relatively difficult task. Adults may fail to recognize the underlying cause and erroneously blame the children's attitude when it comes to handwriting problems.

Generally, the identification of children with HWD required assessment and evaluation carried out by qualified professionals, usually occupational therapists or psychologists, through various formal handwriting assessment test [3]. These conventional handwriting assessment tests, such as Concise Assessment Scale of Children's Handwriting (BHK), Motor-free Visual Perception Test (MVPT), Developmental Test of Visual-Motor Integration (DTVMI), and Minnesota Handwriting Assessment Test (MHA), use different criterion for evaluation, either by analysis of drawing task or handwriting task, or through specific designed question. A threshold value is used in these assessment tests to differentiate children with and without HWD.

Another alternative is to engage experienced teachers to observe the students as they write because teachers can have access to these children in an unobtrusive environment. The teachers are usually used as first stage screening method for HWD instead of obtaining direct diagnosis from qualified clinician. According to survey by Hammerschmidt and Sudsawad [5], most of the teachers from elementary school in United States will refer their students to occupational therapist as having possibility of HWD only when students did not show any improvements after additional assistance, for example, showing continual decrease in handwriting speed, or increasing frustration towards handwriting task. Problematic handwriting was identified by teachers from visual analysis of written products in terms of legibility, letter size, and letter spacing.

The assessment methods carried out by professionals and experienced teachers, whether through daily observations or formal handwriting assessment test, rely highly on individual's subjective evaluation and experience. To avoid the subjectivity in assessment and reduce the dependency of professional manpower that is limited and less accessible, the development of computerized handwriting assessment tool had been proposed to objectively quantify the evaluation of handwriting performance for identification of HWD. This type of system can generalize the assessment of HWD and also provides a convenient screening for early detection of HWD.

Our work aims to develop a HWD identification method based on the dynamics of alphabets formation, including type and direction of strokes used to form the alphabet. This paper presents the algorithm to determine the type of trajectory and sequence of stroke when an alphabet is written. The sequence is then compared with conventional writing method for writing skill assessment. In the following sections, some developed computerized assessment tools will be discussed. The proposed assessment methods will be briefly described, together with the flow of algorithm used to identify the stroke and direction of stroke written. The results of stroke identification using proposed algorithms will be discussed.

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II. RELATED WORKS

Research on computerized handwriting assessment system had been made possible due to increased reliability and quality of digitizer input devices, such as digitizing tablets that capture handwriting data. The computerized tools can be an alternative form of handwriting assessment test. This option reduces dependency on subjective evaluation scores by experts and is capable of sensing or recording parameters unable to be calculated through manual observation. Computerized assessment provides a convenient method to detect possibility of HWD problems at an early stage.

There is several computerized handwriting assessment system that had been developed for this purpose. Longstaff and Heath [6] developed a system that evaluates the handwriting of adults according to the space-time variability between writers. The study revealed that non-proficient adult handwriters had greater space-time variability in their written output than proficient writers. The experimental results may not be applicable to children since handwriting development varies between children and adults.

Brina et al [7] used dynamic time warping (DTW) method as the assessment for poor handwriting among children. The difference between shapes of the written character with reference character was calculated using DTW method, together with other parameters including writing speed and pen pressure exerted during writing. The results showed that children who write with higher shape variability, reflected through greater DTW distance between written and reference character, can be identified as children suffering from HWD problem. This method provided an objective measurement of legibility in written product through comparison with reference character. However, a suitable threshold value needed to be set to differentiate between proficient and non-proficient writers to optimize the system in clinical settings. This threshold may vary depending on population as children in different regions may write alphabets in different ways.

Both Longstaff [6] and Brina's [7] assessment tools used only single parameter to evaluate handwriting performance. Falk et al. [8] developed an assessment tool based on a criteria of quality scores used in Minnesota Handwriting Assessment (MHA) Test. The system used digital tablet and pressure sensor to record xy-coordinates of written product and pencil grip force as measurement input. The criteria in MHA test system are objectively quantified and included legibility, form, alignment, size and space. Together with the analysis of grip force and other temporal parameters, the system could be utilized as a screening tool for identification of children with HWD.

Similarly, the Computerized Penmanship Evaluation Tool (ComPET), as known as Penmanship Objective Evaluation Tool (POET) computed temporal parameters from input of digitizing tablet to distinguish between proficient and non-proficient users [9], [10]. The system computed and analyzed various temporal parameters such as total time used, time used per character, 'in-air time', and speed of handwriting. The results indicated that 'in-air' time, which was the duration when pen tip was away from written surface, can be used to identify children with HWD. According to the research, children suffering from HWD will spend additional in-air time than those who did not have HWD.

Rosenblum et al. integrated additional features of spatial measurement into ComPET, for example, pressure based segmentation algorithms [11]. The algorithm was used to segment out 'single, fluent' unit when writing Hebrew alphabets for analysis. Experiment using the system showed that besides requiring longer 'in-air time', children with HWD produced more 'raw segments' and 'direction reversal segment' than normal children. This opened up a possibility of analyzing segmented trajectories from written characters to assess handwriting.

These digitized handwriting assessment tools could objectively quantify handwriting qualities to evaluate HWD based on temporal and spatial information, such as legibility, character form, and also formation of characters. Our method adds on to these works by assessing children's handwriting dynamics in writing Latin alphabets. The proposed algorithm will identify the type and direction of stroke involved in forming alphabets, and cross referenced them with conventional alphabets formation rules as taught in school.

III. METHODOLOGY

Our method will assess children's handwriting by identifying and analyzing the strokes involved in alphabet production based on the hypothesis that children who do not possess HWD problem should write according to conventional alphabet formation rules in terms of type, direction, and sequence of stroke segments. The general process of the proposed assessment method is illustrated in Fig. 1.

The system accepts point series of written alphabets in xy-coordinates as input, and records them according to the written sequences. The relationship between each consecutive pair of points is analyzed to categorize the written strokes into different categories for further analysis. The type of strokes written and the direction used to produce the corresponding stroke is then determined. The stroke information obtained from the proposed algorithm will be compared with conventional alphabets writing rules, where children who do not write according conventional rules will be categorized into group with possibility of suffering from HWD. The algorithm used to determine the type and direction of writing strokes will be described in detail in the following sections.

A. Classification of Stroke Pattern

Three categories of input stroke pattern are defined in the algorithm, which are (a) simple straight lines, (b) curve, and (c) complex straight lines. Simple straight line are single directional lines that includes vertical (|), horizontal (−), or oblique lines (/ or \). Complex straight line is defined as combination of two or more simple straight lines completed within one single stroke, such as ∟, <, ∧, V, 7 or Z. Strokes that contain curvature, including circle and semicircle will be categorized as curve line.

To effectively identify the input stroke pattern, the input stroke will first be classified into the three defined categories prior to analysis. The classification is done by first computing the production angle θ between each consecutive point, with the previous point used as the reference point. Fig 2. shows the computation of θ between points pt1 and pt2, where p2 is the point recorded after p1.

The set of angle differences, $|\theta - \theta_0|$, is later computed as the feature used for classification of input pattern. This is done by computing the differences of current angle, θ from the angle between first two points, θ_0. These angle differences are used to differentiate the type of stroke involved according to the classification rule below:

- Simple straight line if all of the $|\theta - \theta_0|$ are less than 30°,
- Complex straight line if there exists abrupt changes in angle difference which indicates corner, i.e. any pair of $|\theta - \theta_0|_k - |\theta - \theta_0|_{k-1}$ with magnitude between 50° and 180°,
- Curve line if otherwise.

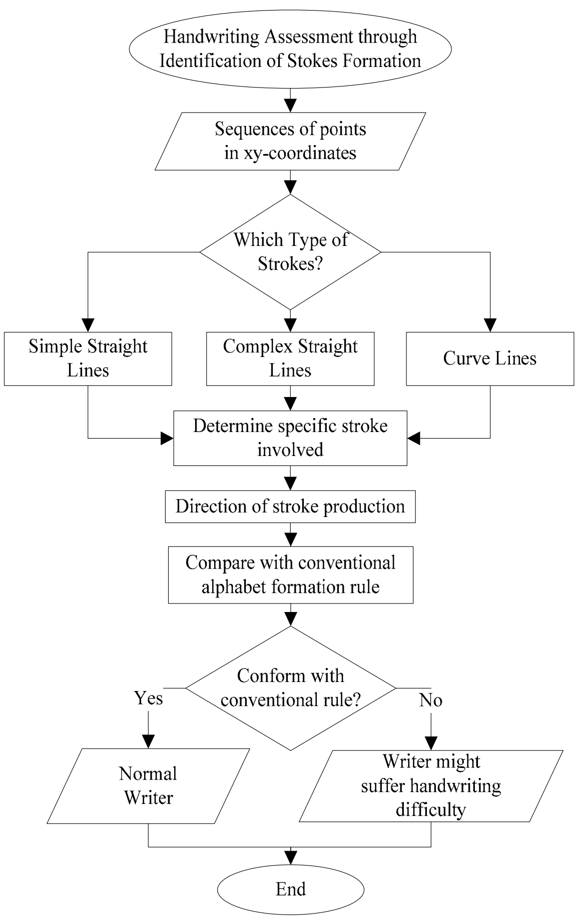

Figure 1. General flowchart of proposed handwriting assessment algorithm.

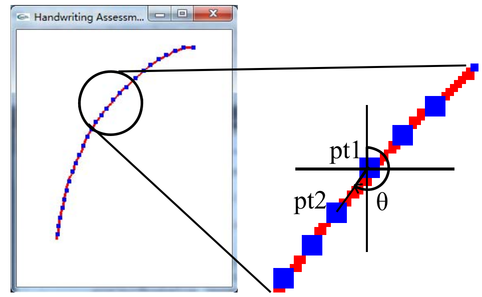

Figure 2. Calculating angle θ between points pt1 and pt2, with pt1 as reference point.

B. *Simple Straight Line*

To determine the type and direction of simple straight lines, the direction of next coordinate from current coordinate is determined according to the directional code in Fig. 3. [12]. The x in the middle refers to the location of current point, and direction of next coordinate is determined with the eight directions ranging from 1 to 8.

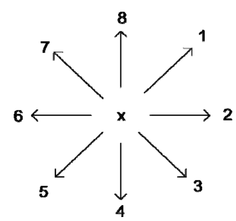

Figure 3. Eight directional code.

The written stroke and direction can be determined according to the analysis of histogram for directional code, in which the relationship between type and direction of stroke with directional code of highest frequency detected is summarized in Table 1.

TABLE I. DIRECTIONAL CODE AND REPRESENTED STROKE TYPES

Directional Code	Shape of Strokes	Type of Strokes	Stroke Direction
1	↗	Left to right oblique line	Upwards to right
2	→	Horizontal lines	Rightwards
3	↘	Left to right oblique line	Downwards to right
4	↓	Vertical line	Downwards
5	↙	Right to left oblique line	Downwards to left
6	←	Horizontal line	Leftwards
7	↖	Left to right oblique line	Upwards to left
8	↑	Vertical line	Upwards

C. *Complex Straight Lines*

Since complex straight lines are composed by different simple straight lines, the identification of complex straight lines can be done using the identical algorithm used for determining simple straight lines. This is done by segmenting the complex straight line into sub-stroke of simple straight lines at the point where abrupt angle difference is detected, that is at point k when $50° < |\theta - \theta_0|_k - |\theta - \theta_0|_{k-1} < 180°$. The segmented sub-stroke can be fed into the algorithms for identification of simple straight line for further analysis.

D. *Curve Lines*

A total of eight quadrants of angle representation are used in order to determine the direction of curve lines as shown below.

1. Q1 when $-5° < \theta < 5°$, which is from 355° to 0°, and 0° to 5°.
2. Q2 when $5° < \theta < 85°$,
3. Q3 when $85° < \theta < 95°$,
4. Q4 when $95° < \theta < 175°$
5. Q5 when $175° < \theta < 185°$,
6. Q6 when $185° < \theta < 265°$,
7. Q7 when $265° < \theta < 275°$, and
8. Q8 when $275° < \theta < 355°$,

The consecutive angles, θ is analyzed relative to the ensuing quadrant, while the changes of quadrant detected are used to determine the direction of curve. For example, quadrants' sequence that follow numerical order 2-4-5 implies a clockwise curve and vice versa.

IV. Results and Discussions

A set of inputs with 10 different input strokes as shown in Fig. 4. were tested using the proposed algorithm. These inputs comprised patterns of simple straight lines, complex straight lines and curve lines drawn using computer mouse. There were two simple straight line inputs (input 1 and 2), four complex straight line strokes (input 3, 7, 8, 9), and three curve lines (input 4, 5, 6), together with another special stroke pattern similar to character 'J' in input 10. The results of the experiment are summarized in Table 2.

For stroke category classification, input patterns had to be categorized into three groups of simple straight line, complex straight line or curve. The inputs 1, 2, 3, 4, 5, 6, 7, and 9 were successfully classified into their stroke categories whereas the input pattern of 8 and 10, which were both supposed to be in complex straight line category, were classified into the curve line category. The failure in classification might be caused by the absence of abrupt change in angle of input patterns therefore, not fulfilling the conditions for detection of complex straight line. For example, the round corner of input 8 between horizontal and vertical sub-stroke cannot be detected as 'sharp' and explicit corner is needed to meet the conditions of abrupt changes in angle difference between 50° to 180° degrees. Input 10 was a special case, where a straight line was joined by a curve resembling 'J'. The system identified this input as a curve based on the ending portion as it did not fulfill the characteristics of complex straight line supposedly formed by two straight-line sub strokes. One possible workaround to this is establishing a new category for such patterns, e.g. straight line with curve sub strokes.

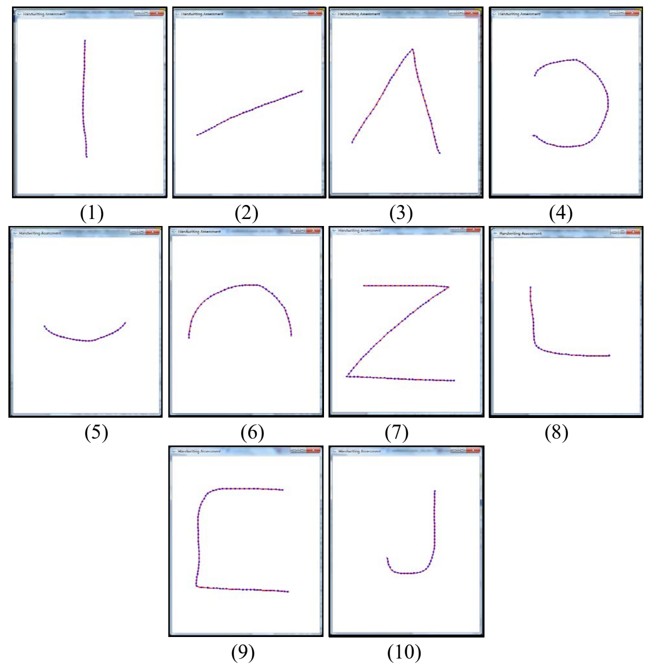

Figure 4. Input stroke patterns 1-4 (above), 5-8 (middle), and 9-10 (below) listed from left to right.

TABLE II. Result of the Analysis For Input Set in Fig. 4.

Input Pattern	Stroke Categories	Type of Strokes	Stroke Direction
1	Simple Straight	Vertical Line	Downwards
2	Simple Straight	Oblique Line	Left to Right, Upwards
3	Complex Straight	1. Oblique Line	1. Left to Right, Upwards
		2. Oblique Line	2. Left to Right, Downwards
4	Curve	-	Clockwise
5	Curve	-	Anticlockwise
6	Curve	-	Clockwise
7	Complex Straight	1. Horizontal Line	1. Left to Right
		2. Oblique Line	2. Right to Left, Downwards
		3. Horizontal Line	3. Left to Right
8	Curve	-	Anticlockwise
9	Complex Straight	1. Oblique Line	1. Right to Left, Downwards
		2. Horizontal Line	2. Left to Right
10	Curve	-	Clockwise

For type of strokes, the detections were successful for simple straight line and some complex straight line inputs. The type of strokes for inputs 1, 2, 3, and 7 were correctly identified. Input 9 that consisted of three sub-strokes (two horizontal lines and a vertical line) was segmented into only two sub-strokes and identified as oblique and horizontal lines. The failure in segmentation is likely due to the round corner of input 9, which was registered as a continuous trajectory. A rigorous test is needed to identify an optimal angle range to detect segments in complex lines.

Similarly, the algorithms show success in identification of stroke direction for curvature, either in clockwise direction or anti-clockwise direction as in inputs 4, 5 and 6. The algorithm has limitation in determining degree of curvature and type of curvature involved, such as curve shapes of ‘c’, ‘u’, ‘n’, and inverted ‘c’, which will be useful for detailed assessment of writing strokes.

V. Conclusion and Future Directions

This paper discusses an algorithm that can be utilized in a handwriting assessment system to identify possible HWD sufferers, especially children. The algorithm analyzes errors in dynamic formation of alphabet based on stroke sequences and directions. This algorithm performs well in classification and identification of simple and complex straight line strokes, while more features are needed to further distinguish curve lines into different shapes of ‘c’, ‘u’, ‘n’, and inverted ‘c’ type, and to detect complex curvature, such as in alphabet ‘S’. When the types and direction of strokes can be determined, a ‘stroke code’ recording all the stroke information can be established and compared with conventional stroke formation methods to determine the errors made. By identifying the errors involved, children who may be suffering from HWD can be identified for early intervention.

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